Calibration of Model Uncertainty for Ensemble Forecast of Ionosphere Conditions

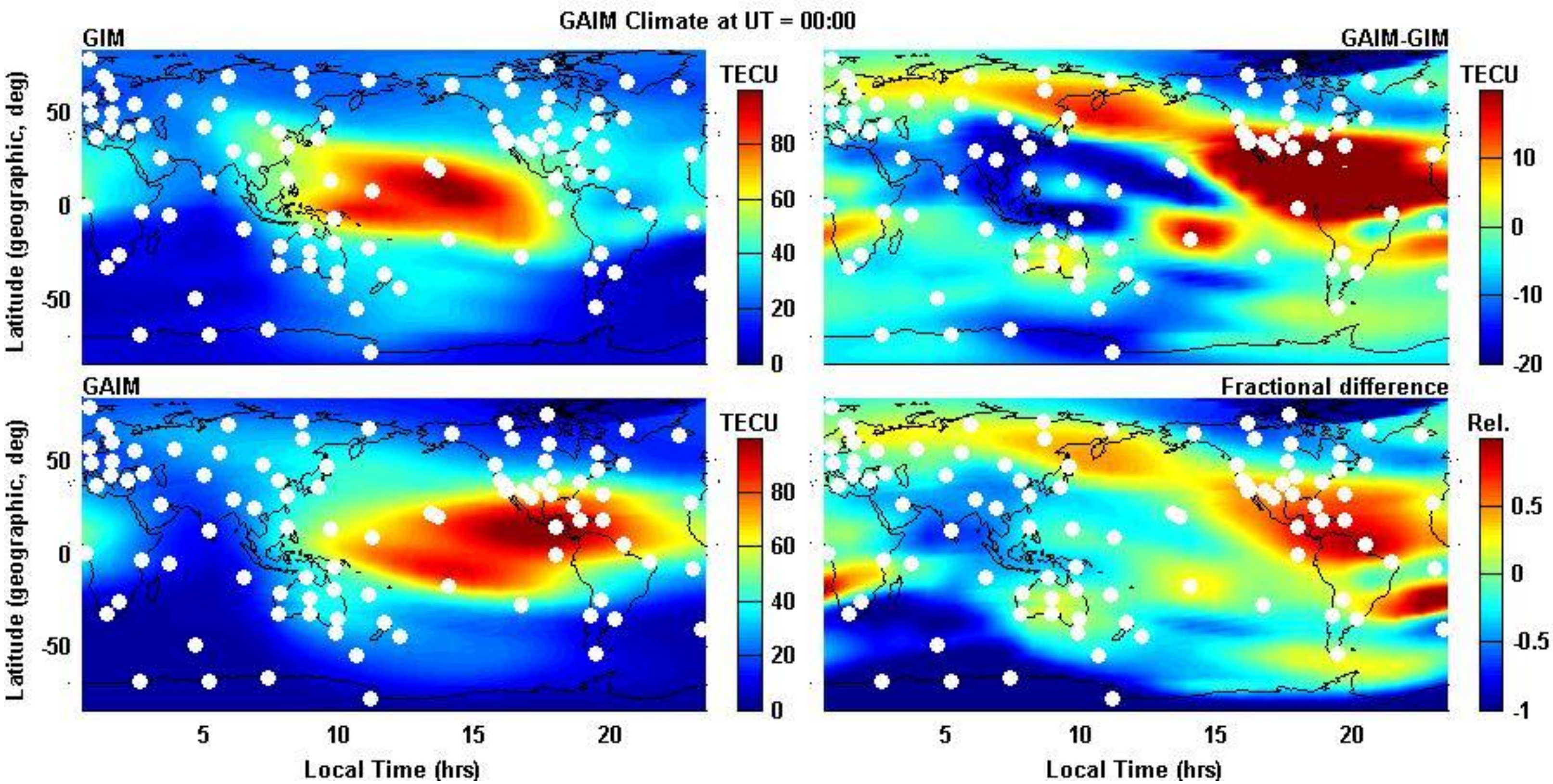
Chunming Wang
Modeling & Simulation Laboratory
Department of Mathematics
University of Southern California

Ensemble Forecast Must Realistically Represent Model Uncertainties

- Ensemble technique allows propagation of uncertainty from suspected sources to model states
- Random or strategic sampling are based on underlying uncertainty models
- Ensemble forecast or data analysis must correctly represents statistical characteristics of the model state such as means and covariance
- Improvement of forecast reduces uncertainty

Calibrated Uncertainty Ensures Realism of Ensemble Forecast

Comparison with Data Driven Models Shows Larger Diversity in Data



- Model must be able to produce observed variability

First Principle Numerical Model is the Primary Tool for Forecast

- GAIM climate model is a first principle, multiple ion model for mid and low latitude region of ionosphere
- Model was developed with data assimilation as part of its design
- Parameterization of driver perturbation and solution of the adjoint equation allows implementation of 4DVAR for driver estimation
- Both Kalman and 4DVAR versions of the JPL/USC GAIM are based on the same first principle model

Model Uncertainty Inherently Corresponds to Unmodeled Physics

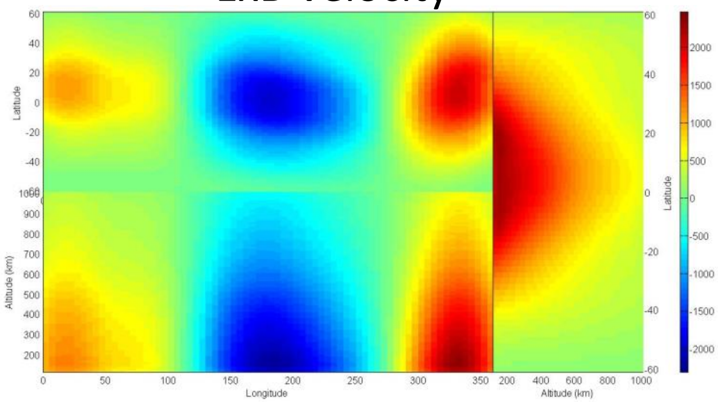
- Approximation of physical laws
  - Simplification of physical laws
  - Spatial and temporal discretization
  - Relatively easy to quantify
- Unknown model parameters
  - Ionosphere drivers such as solar irradiance, neutral density, temperature and velocity
  - Initial conditions of the system
- Unknown mechanism influencing the dynamics

Primary Sources of Uncertainty Come from Unknown Parameters

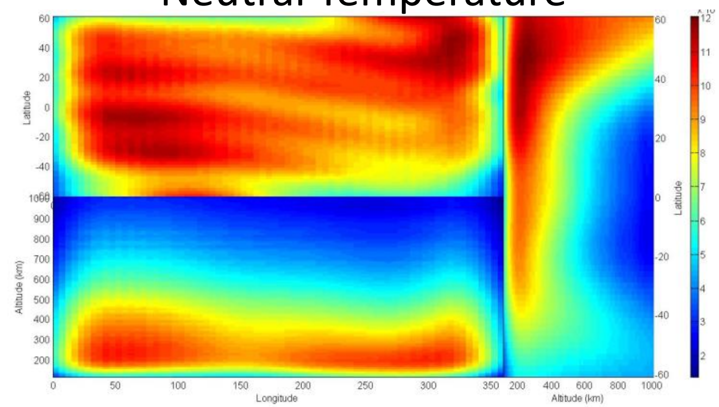
- Model of the ionosphere strongly dependent on external driving forces that are poorly known
- Statistical values of these parameters are often used in forecast model
- Effect of randomness of driver parameters on the model states are mostly nonlinear and globally correlated
- Understanding of the uncertainty can lead to improvement of forecast and data assimilation

Number of Parameters Provides Sufficient Degree of Freedom

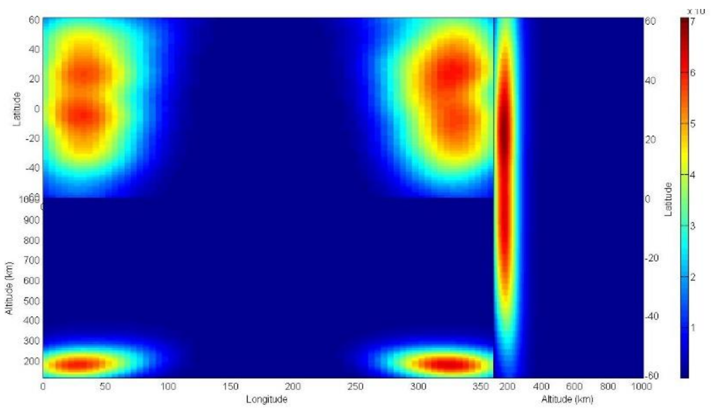
ExB Velocity



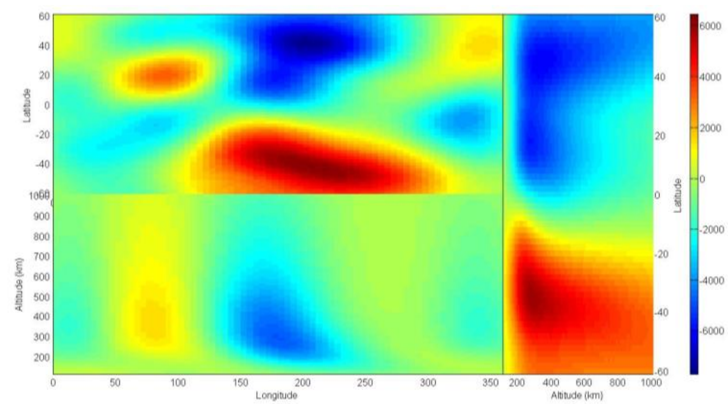
Neutral Temperature



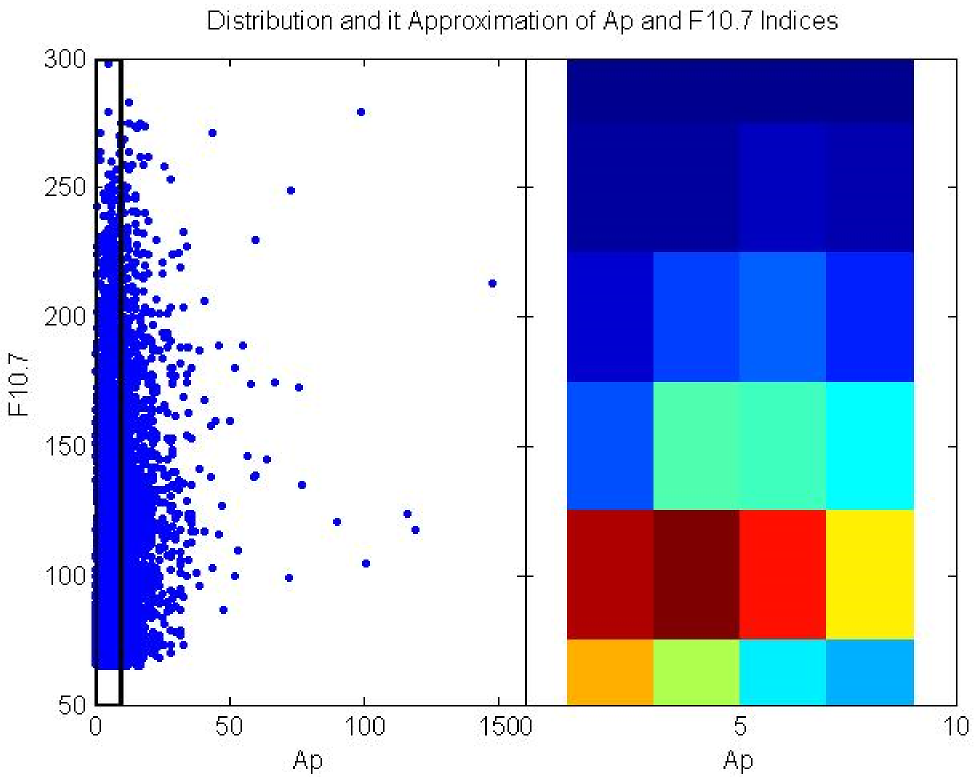
Production Rate



Neutral Wind Velocity



Ensemble Based on Solar Indices Serves as Baseline for Forecast Performance

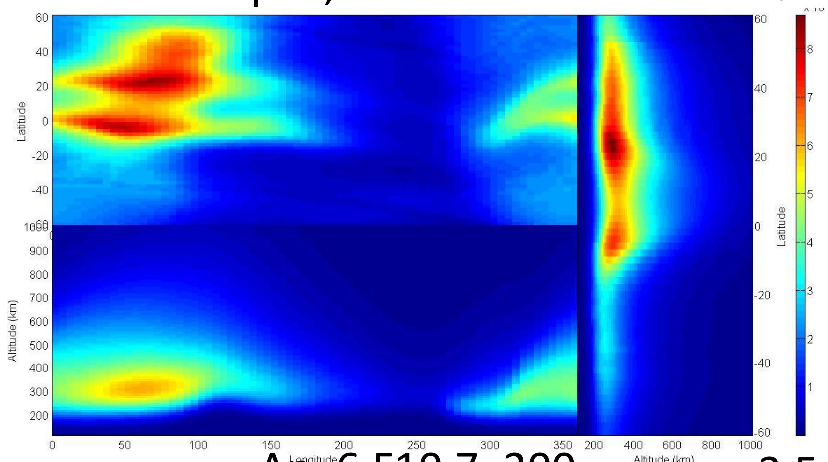


Sampled area represents over 60% of quite conditions. Index data from 1997-2012

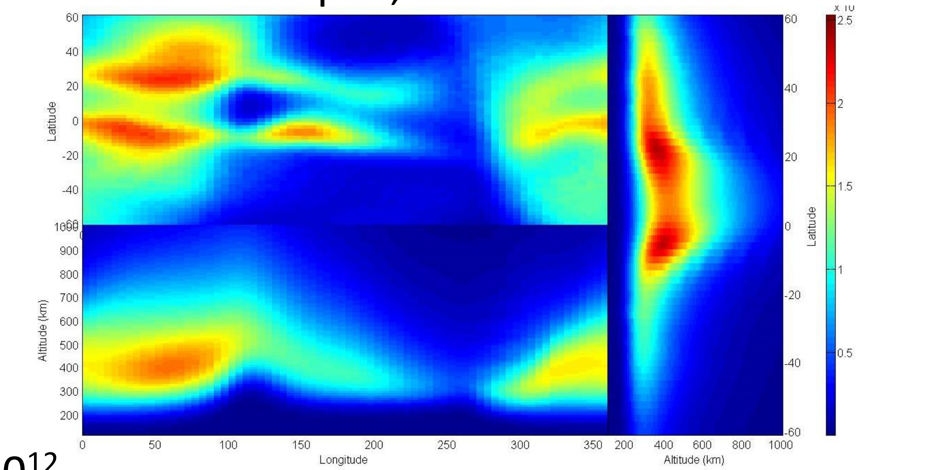
- "Prediction" is for April 25, 2011
- Ensemble of index values covers large number of historic cases
- Limit data to solar minimum conditions or data from a specific season reduces diversity

Large Scale Changes Are Reproduced by the Ensemble Forecast

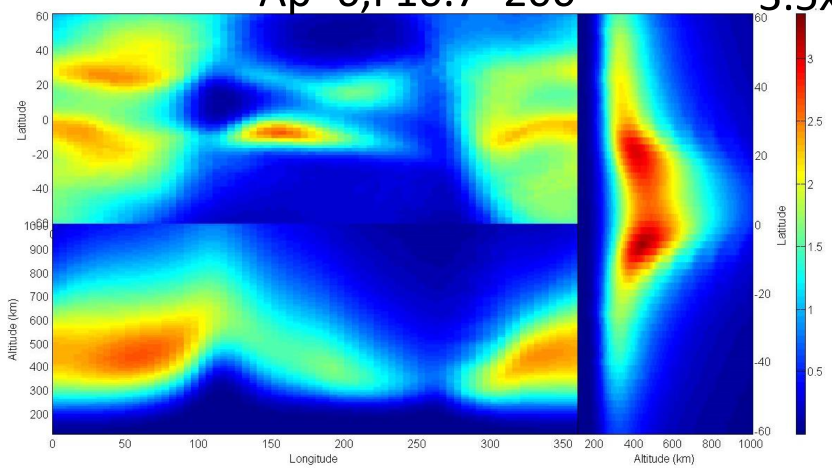
Ap=2,F10.7=50 $8x10^{11}$



Ap=4,F10.7=150 $2.5x10^{12}$



Ap=6,F10.7=200 $3.5x10^{12}$



Expected variability is observed in predictions made using different values of indices

First Principle Analysis Identifies Key Components of Deviation from Mean

- Small ensemble size does not allow accurate characterization of covariance of model prediction
- Principle Component Analysis computes singular vectors of the empirical covariance matrix
- The leading Principle Components may still be representative of the main characteristics of the deviations from the ensemble mean
- Principle Components form an orthonormal basis that captures all deviations from mean

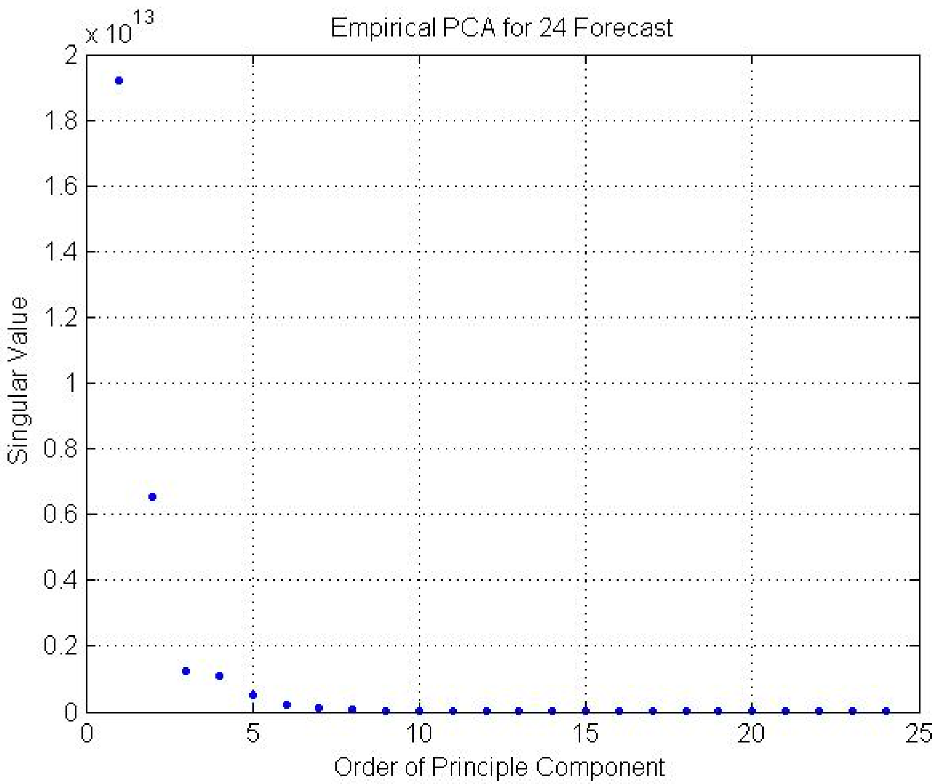
Principle Component Analysis Helps Quantifying the Degree of Variability

- PCA can be relatively easy to perform when the ensemble size is small

$$D = [f_1, \cdots, f_n], T = D^T D, T v_k = s_k^2 v_k$$
$$PC_k = D v_k$$

- Singular values s_k represents the degree of variation of the projection onto the associated PC
- When the values of s_k drop off rapidly, the data has low overall variability

Only a Very Small Number of Principle Values are Over 1%

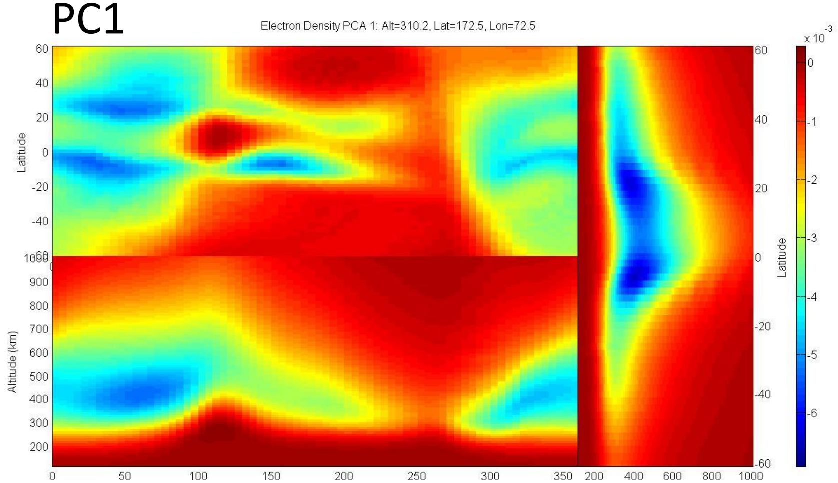


Principle Components of deviation from ensemble mean is also affected by the selection of the ensemble

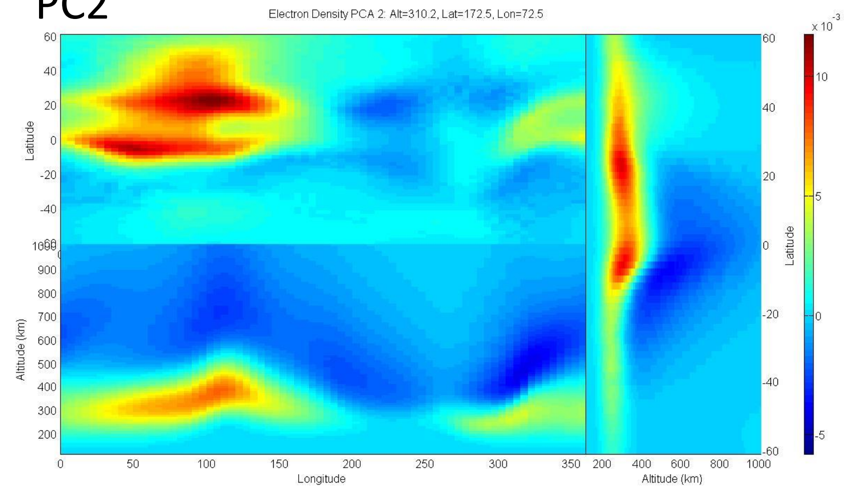
- Singular values of relative to the leading SV provides significance of the PC
- Principle components may be linked to specific weather effect
- The most interesting weather event may by linked to secondary PCs

Principle Components Show Interesting Features

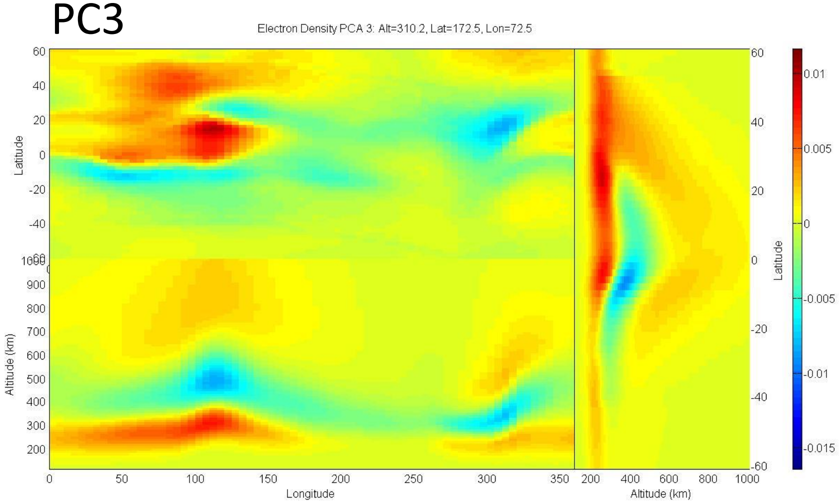
PC1



PC2

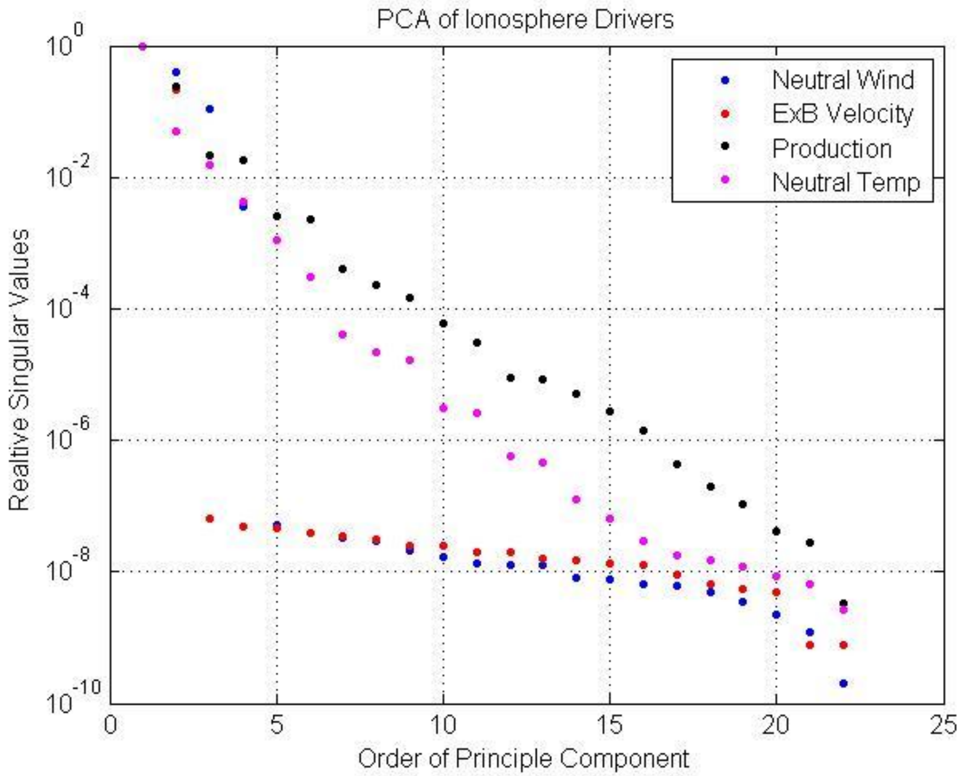


PC3



- The leading components shows nonlinear effects of random drivers: mean field is larger than most data at noon local time

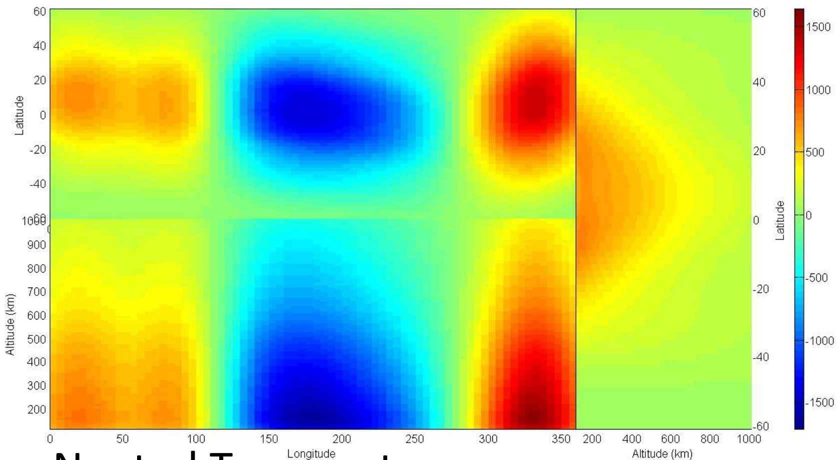
Small Number of Significant PCs May be Due to Small Driver Variability



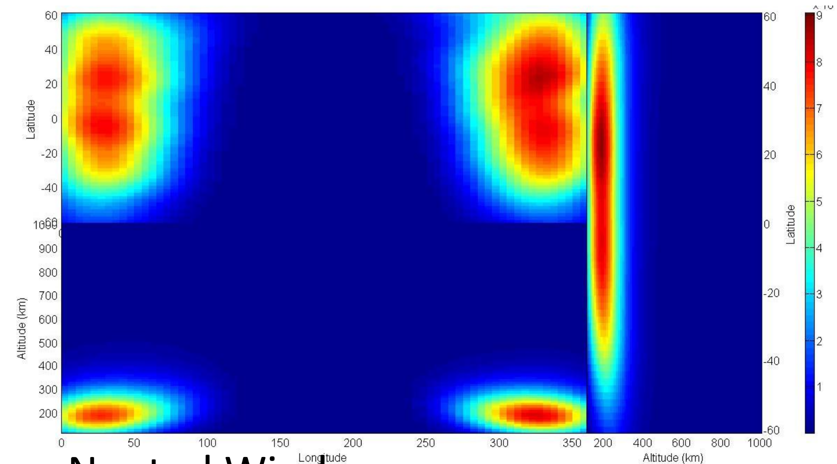
- Sample of 4 key drivers shows less than 5 PC with larger than 1% of relative singular values
- Alternative driver models may lead to additional variability

Mean Driver Fields Represent the Overall Characteristics

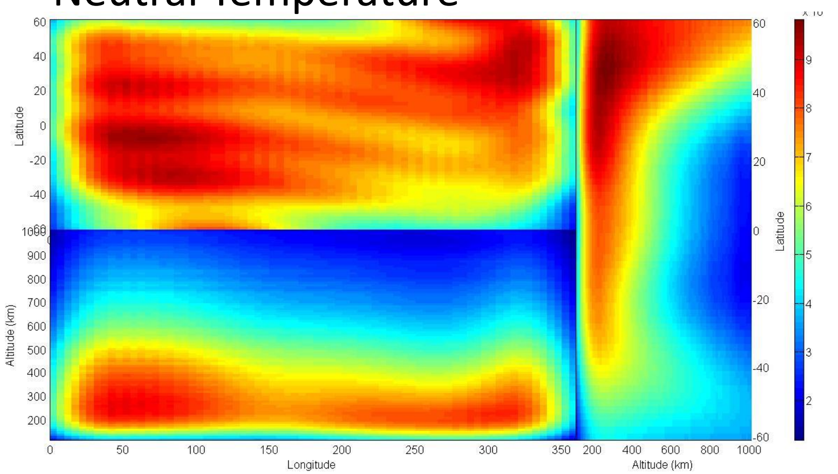
ExB



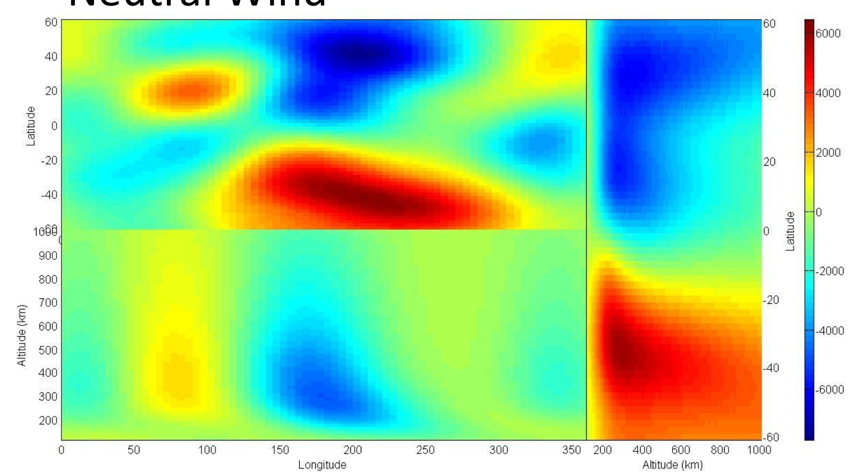
Production



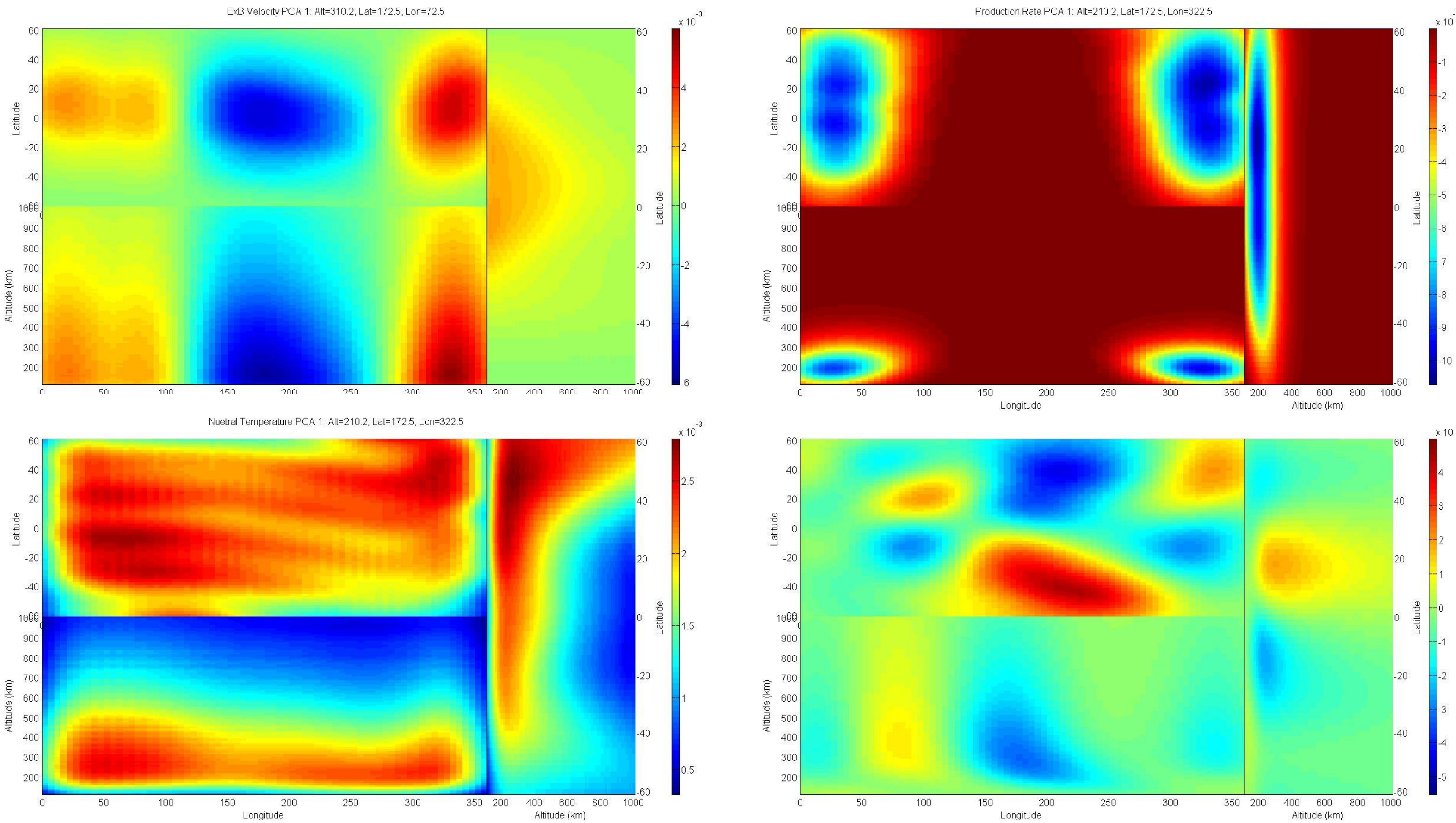
Neutral Temperature



Neutral Wind



Leading Principle Components of Driver Fields Are Dominant



Modeling & Simulation Laboratory

Small Variability in Model Output Limits Ability to Forecast

- Is small variability inherent in any model that relies on a small number of observations of space environment?
- Can ensemble of models for the drivers help address the problem of small variability?
- How can we calibrate variability due to unmodeled physics in ionosphere and its drivers?
- Does data assimilation offer hope for increasing variability in driver and model output?

Conclusion

- Simple ensemble forecast experiment reveals low model variability of climatological models for drivers and ionosphere electron density
- Characterization of the principle components based on ensemble simulation shows interesting features
- Identifying the principle components of the drivers can significantly improve efficiency and accuracy of ensemble forecast
- Current analysis can be applied to other models